

Climate sensitivity of global terrestrial ecosystems' subdaily carbon, water, and energy dynamics

Rong Yu¹, Benjamin L. Ruddell^{1,2}, Daniel Childers² & Minseok Kang³

¹Fulton Schools of Engineering, Arizona State University, USA

²Julie Ann Wrigley Global Institute of Sustainability, Arizona State University, USA

³National Center for AgroMeteorology, Seoul National University, South Korea

This material is based upon work supported by the National Science Foundation under Grant No. 1241960; findings are those of the authors and not necessarily the NSF.

1. Introduction

Under the context of global climate change, it is important to understand the direction and magnitude of different terrestrial ecosystems respond to climate at the global level. In this study, we constructed eco-climate system dynamical process structure by using the eddy covariance measurements (subdaily net ecosystem exchange of CO₂, air temperature, and precipitation) from the FLUXNET and by employing dynamical process network (DPN) approach. Then, the eco-climate system sensitivity model was applied to estimate the eco-climate system elasticity to climate and biophysical factors at the flux site level. For the first time, eco-climate system elasticity was estimated at the global flux sites and extrapolated to all possible land covers by employing artificial neural network approach and by using the MODIS phenology and land cover products, the long-term climate GLDAS-2 product, and the GMTED2010 Global Grid elevation dataset. This study has the potentials to 1) provide the global eco-climate system sensitivity/vulnerability products; 2) conduct short-term and long-term forecasting of eco-climate system transitions; 3) complement dynamic global vegetation and climate models; and 4) serve for eco-climate system management and policy making.

2. Data and methods

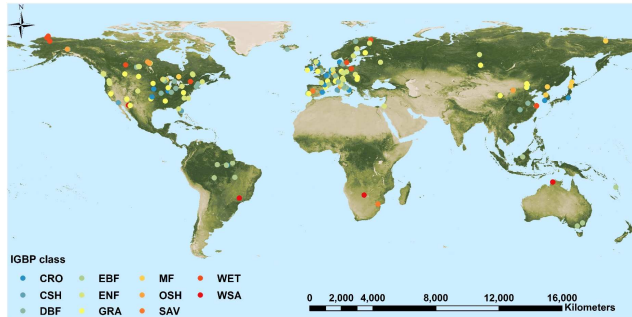


Figure 1 Global eddy covariance flux sites used in this study and their International Global Biosphere Programme (IGBP) vegetation class. CRO: croplands; CSH: closed shrublands; DBF: deciduous broadleaf forests; EBF: evergreen broadleaf forests; ENF: evergreen needleleaf forests; GRA: grasslands; MF: mixed forests; OSH: open shrublands; SAV: Savannas; WET: Wetlands; WSA: woody savannas. Base map: the MODIS NDVI retrieved between 07/28/2014 and 08/13/2014 from the NASA Earth Observations.

Dynamical process networks:

1. Shannon entropy (H) (Shannon 1948)

$$H(Y_i) = -\sum_{y \in Y_i} p(y) \cdot \log p(y)$$

where $p(y)$ is the prior probability that discrete variable Y takes state y .

H^* (normalized H): $H^* = H/\log(m)$, where m is the number of bins used to discretize the probability density function.

2. Transfer entropy (T) (Schreiber 2000)

$$T(X_t \rightarrow Y_t, \tau) = \sum_{y_t, y_{t-1}, \dots, y_{t-\tau}} p(y_t, y_{t-1}, \dots, y_{t-\tau}) \log \frac{p(y_t | (y_{t-1}, \dots, y_{t-\tau}))}{p(y_t | y_{t-1})}$$

Modeling the eco-climate system sensitivity to climate and biophysical factors at the site level:

$$T^* = \alpha \cdot \bar{\theta}^{\beta_{\theta}} \cdot \bar{P}^{\beta_P} \cdot \bar{R}^{\beta_R} \cdot \bar{EVI}^{\beta_{EVI}}$$

$$C_{\bar{E}} = \beta_{\bar{E}} + \gamma_{\bar{P}} \ln \bar{P} + \gamma_{\bar{R}} \ln \bar{R}$$

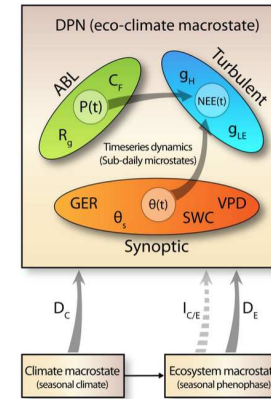
$$T^* = \ln \alpha + \beta_{\theta} \ln \bar{\theta} + \beta_P \ln \bar{P} + \beta_R \ln \bar{R} + (\beta_{\bar{E}} + \gamma_{\bar{P}} \ln \bar{P} + \gamma_{\bar{R}} \ln \bar{R}) \cdot \ln \bar{EVI}$$

In the first equation, $\bar{\theta}$ is standardized monthly mean air temperature; \bar{P} is standardized monthly total precipitation; \bar{R} is standardized monthly mean global radiation; \bar{EVI} is monthly mean remotely sensed phenological parameter; α is a constant; β_{θ} , β_P , β_R , and $\beta_{\bar{E}}$ are the elasticities of T^* with respect to $\bar{\theta}$, \bar{P} , \bar{R} and \bar{EVI} , measuring the DPN coupling response to change of climate forcings and ecosystem state.

In the second equation, $C_{\bar{E}}$ (elasticity of \bar{EVI}) is estimated using a random coefficients model to differentiate direct control of phenology on DPN and indirect controls of climate via phenology on DPN.

In the third equation, α , β_{θ} , β_P , β_R , $\beta_{\bar{E}}$, $\gamma_{\bar{P}}$ and $\gamma_{\bar{R}}$ can be estimated for each site by using ordinary least squares (OLS) as coefficients of a linear regression function

Figure 2 Conceptual framework illustrating the terrestrial ecosystem's eco-climate macrostate as a Dynamical Process Network (DPN) comprised of couplings between three functional subsystems (Synoptic, Turbulent, and ABL). This DPN simplifies relationships between the three subsystems by using the two couplings $P \rightarrow NEE$ and $\theta \rightarrow NEE$ to approximate the full network structure. Seasonal scale climate and phenophase determine the DPN structure via direct and indirect pathways. The three pathways are: D_C – direct control of seasonal climate on the DPN; D_E – direct control of seasonal phenophase on the DPN; and $I_{C/E}$ – indirect control of climate on the DPN via phenophase.



Simulating the eco-climate system sensitivity to climate and biophysical factors at the global level:

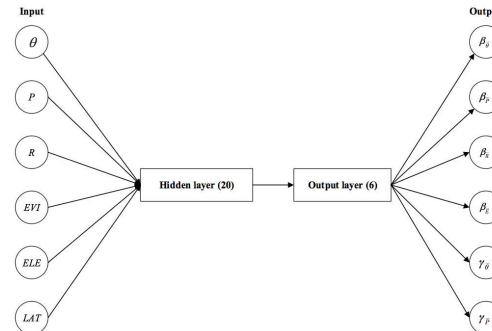


Figure 3 Schematic diagram of NN. Input variables (long-term averages): θ (air temperature), P (precipitation), R (incident shortwave radiation), EVI , ELE (elevation), and LAT (absolute latitude). Output variables: β_{θ} (coefficient of the direct control of air temperature on eco-climate system coupling), β_P (coefficient of the direct control of precipitation on eco-climate system coupling), β_R (coefficient of the direct control of global radiation on eco-climate system coupling), β_E (coefficient of the direct control of phenology on eco-climate system coupling), γ_{θ} (coefficient of the indirect control of air temperature on eco-climate system coupling), and γ_P (coefficient of the indirect control of precipitation on eco-climate system coupling).

3. Results

(1) Monthly patterns of eco-climate system DPN

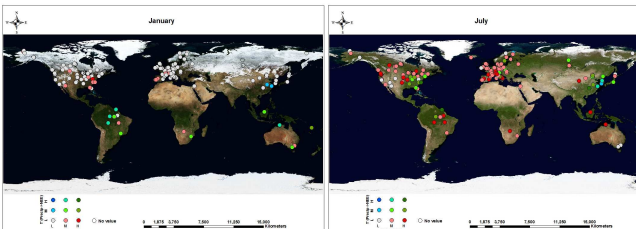


Figure 4 Examples of monthly variation of eco-climate system DPN (January and July). $T^*(\theta \rightarrow NEE)$: L: 0.003141; M: 0.003141; H: 0.006837; G: 0.016024. $T^*(P \rightarrow NEE)$: L: 0.000137; M: 0.000137; H: 0.000558; G: 0.001562. The classification method for $T^*(\theta \rightarrow NEE)$ and $T^*(P \rightarrow NEE)$ is Jenks natural breaks in ArcGIS 10.3 for Desktop, which has the ability to maximize class differences.

(2) Elasticity of DPN coupling strength to seasonal climate and phenological states

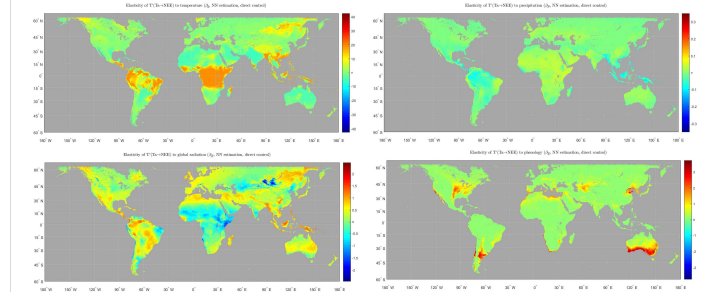


Figure 5 Examples of elasticity maps for the temperature-NEE coupling to long-term averaged seasonal climate and phenological states.

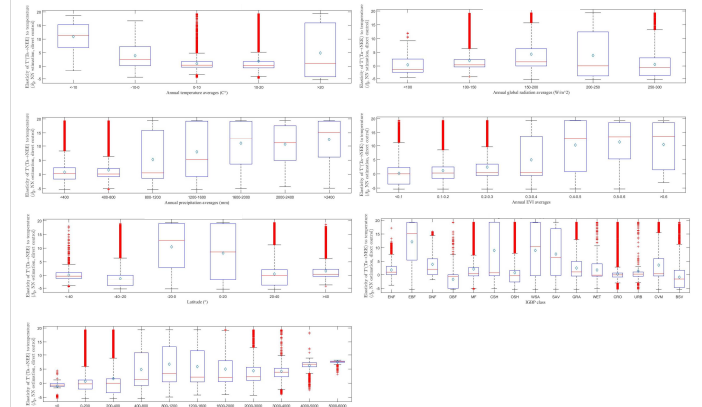


Figure 6 Examples of boxplots of the sensitivity of the temperature-NEE coupling to each individual climate and biophysical factor based on grouped long-term annual temperature, precipitation, global radiation, and EVI, as well as latitude, elevation, and IGBP class.

4. Summary

- In general, the couplings and their magnitudes varies seasonally over regions. These seasonal variations of DPN structure of eco-climate systems illustrate the scaled-up influence of fast dynamics of temperature and precipitation on carbon.
- The temperature elasticities of eco-climate system temperature-NEE coupling were highest compared to the other climate and biophysical factors, which means that for the same percentage change on the climate and biophysical factors, the change of temperature could lead to the biggest change on temperature-NEE coupling. Therefore, this coupling is most sensitive to temperature.
- The relationships between the elasticities of eco-climate system and the climate, environmental and ecological features are complex. It varies among the different combinations of sensitivities and features.
- The temperature-NEE coupling was more sensitive to climate and biophysical factors, except precipitation, than the precipitation-NEE coupling.
- Generally, the eco-climate system dynamical process structure we built in this study is more sensitive to temperature, whether directly or indirectly via phenology.
- Interestingly, if temperature continues rising, the temperature-NEE coupling may increase in tropical rainforest areas while decrease in tropical desert or Savanna areas, which may suggest that rising temperature in the future could lead to more carbon sequestration in tropical forests whereas less carbon sequestration in tropical drylands.
- Phenology showed a positive effect on the temperature-NEE coupling at all pixels, which suggests increased greenness may increase temperature driven carbon dynamics and consequently carbon sequestration globally.